Mathematical Model of The Heart Rate

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Abstract

The objective of the present study was to formulate an effective mathematical model of heart rate adolescents, in religious environment with similar activities like mindfulness. Based on an existing model, a system of two coupled differential equations which give the rate of change of heart rate. The modifications introduced to the existing model are justified and discussed. The environment, daily activities, as well as mood are also taken into account. Application of the model provides information regarding the individual's heart beat and is able to detect next beat from the last two beats found in the data. To demonstrate examples of successful numerical fit of the model, heart rate data sets of two individuals have been selected and numerical optimization was implemented. The proposed model can serve as a powerful tool for a complete means of heart rate analysis, not only in daily activities, but also in the areas of cardiovascular health.

Keywords: *heart beat; mood; circadian rhythm, mathematical model; morningness.*

1. Introduction

The heart rate is one of the 'vital signs,' or the significant gauges of health in the human body. It measures the amount of times per minute that the heart contracts or pulses. The pace of the heartbeat varies as a result of physical activity, threats to safety, and emotional responses [1] Even if individual is not an athlete, knowledge about individual's heart rate can help him monitor his fitness level — and it might even help him spot developing health problems [2]influenced by emotion like freez ….disgust….angry…. hostility can ruin your heart rate.

Most psychophysiological disorders as a consequence of stressful situations depend on triggered physiological responses and activated organs. Physiological activity causes wear and tear in the organs concerned (fatigue). The higher the frequency, intensity and duration of the response triggered by a stressful situation, the greater the likelihood of interference. Individuals who have strategies to deal with stressful situations will be able to cope with stress and minimize the possibility of the appearance of psychophysiological disorders. Response to stress is not a bad thing, because it facilitates access to more resources to overcome various situations. But if resources are often spent in large quantities, especially if sustainable, this involves significant debilitation for individuals.

Stress can produce negative, anxiety, anger, fear, sadness or other emotional reactions. Anxiety is an emotion that causes a fear reaction to anticipate a danger or threat, accompanied by activation of the autonomic nervous system. responses to fears of unknown or uncertain things are generally found in stressful situations. Therefore stress that occurs repeatedly has a negative effect on health. There is a lot of evidence that shows the influence of stress on health, including cardiovascular problems, infections, or exacerbations of existing problems (when stressed the individual's weak points are greatly affected, such as eczema, back pain associated with tension, migraines, colds, etc.)[3]

Evidence supporting hypothesis that humor, gratitude and savoring may all share an underlying common characteristic that could drive greater positive cognitive appraisals. Savoring, in turn, is an important strategy for maintaining and amplifying the experience of positive emotions (e.g., happiness)[4]

Understanding human heart rate is important matter interpretation and analysis is fundamental not only to our knowledge of cardiovascular health and rehabilitation, but also for fitness.
Data Set. It should be noted here that raw heart rate data, recorded on a beat-to-beat basis are necessary for the development of a model: a model which is fit to averaged data is not necessarily a good model of the raw un-averaged data. It is widely accepted that beat-to-beat recordings exhibit spontaneous fluctuations which may have biological significance, as non-linear systems such as the one that governs the circulatory function can produce signals which look like random noise but are in fact not stochastic. Therefore part of what is attributed to noise can contain inherent features and vital information
Growing evidence shows that cardiovascular functions are related to intrinsic circadian clocks. The diurnal changes in blood pressure and heart rate are well known circadian rhythms. These rhythms produce changes in variables such as body temperature, various hormone levels, and the sleep–wake cycle.
This pattern of activities in the morning or evening is associated with biological signs at the respective time of day [5]. Phase estimation of the human circadian rhythm is a topic that has been explored using various modeling approaches. The current models range from physiological to mathematical, all attempting to estimate the circadian phase from different physiological or behavioral signals. Here, we have focused on estimation of the circadian phase from unobtrusively collected signals in ambulatory conditions using a statistically trained autoregressive moving average with exogenous inputs (ARMAX) model. Special attention has been given to the evaluation of heart rate interbeat intervals (RR intervals) as a potential circadian phase predictor [6].

In this framework, Jessica, Margaret, Rasmussen, Smiley and Hellemann documented bidirectional associations between parental over control (OC) and children's anxiety; over control OC may place children at risk for anxiety and also may occur in response to children's requests for help. for higher anxiety mothers themselves, engaging in OC will be associated with reductions in physiological reactivity (decreases in heart rate) [7].
Mantantzis, Maylor, and Schlaghecken. examined whether glucose can help older adults to exert more effort under high difficulty conditions. Fifty-three young and 58 older adults consumed a glucose or glucose produced increased heart rate (indicating higher task engagement) [8]. Tracy, Gerardo, and Koenig found that Sex differences in resting Heart Rate Variability (HRV) exists such that women typically exhibit higher resting heart rate variability (HRV) than men [9].

Sassenrath, Wagner, Keller, and Sassenberg found what feeling with another person findings suggest that coping-related appraisal processes influence how the empathizing individual reacts in terms of cardiovascular reactivity. This, in turn, provides novel insights regarding the affective-motivational outcomes of empathy [10]. However, research has not yet considered how individual differences in both emotion regulation abilities, as indexed by resting high-frequency heart rate variability (HF-HRV), and rumination, The following investigation examined this relationship in a sample of 101 college-aged students (45 AAs and 56 Caucasian Americans). Resting HF-HRV was assessed via electrocardiogram during a 5-minute-resting period. [11]. Wendt, Weymar, Junge, Hamm, and Lischke examined during social interactions, Memory formation of salient stimuli like untrustworthy faces may be modulated by the interplay between the autonomic and central nervous system, which can be indexed by changes in vagally mediated heart rate variability (HRV). To test this assumption, they investigated whether differences in heart rate variability **(**HRV**)** would be associated with differences in memory formation of untrustworthy faces in a sample of healthy participants. Across participants, increased memory accuracy for untrustworthy faces was associated with increased heart rate variability **(**HRV**)** [12].

Nasso, Vanderhasselt, Demeyer, and Raedt setting goal of their study was twofold: first, the authors compared the influence of adaptive versus maladaptive anticipatory emotion regulation (ER) on the autonomic system during anticipation of, confrontation with, and recovery from a stressor. Trait rumination levels moderated the effect of anticipatory ER strategy on heart rate variability (HRV) during the stressor phase. high ruminators demonstrated lower heart rate variability (HRV) in that same condition. [13].

Katharina Rombold-Bruehl, Katja Wingenfeld concluded thatsome people develop symptoms of post-traumatic stress disorder (PTSD) after having experienced a traumatic event, Least absolute shrinkage and selection operator regression revealed salivary cortisol, salivary -amylase activity, heart rate variability (HRV), subjectively rated distress, fear, and (on trend level) dissociation during the trauma film as relevant predictors of intrusive memories. A heightened biological stress response in young women is associated with more intrusive memories the first days after experiencing a trauma analogue[14].

Heart Rate Reveals the Difference Between Disgust and Anger in the Domain of Morality Konishi and Kochi investigated the potential of distinguishing disgust from anger by changes in heart rate (HR) in the domain of morality. they measured participants' HR while they read a series of moral violation scenarios. The results of three studies (Pilot Study 2, Study 1, and Study 2) demonstrated an association between decreased HR and disgust in response to moral violations. Anger tended to be associated with increased HR, but this association occasionally failed to reach statistical significance. Study 2 also revealed that anger provoked both direct and indirect punishment, whereas disgust provoked indirect punishment and distancing from the transgressor[15].

There are many benefits from mathematical modeling for biopsychology. For example The benefit of mathematics in biopsychology has led researchers that may be able to reveal the architecture of the human genome. And how DNA is organized and accessed. in Japan to a formula that can describe the movement of DNA inside living human cells. In this research an autoregressive model will be used. This is a time series model that is often used to model data in different areas of biopsychology. The autoregressive model (AR) is a flexible model by setting the order and model parameters and in psychology usually used for longitudinal studies [16][17]. Other study revealed bidirectional influence Between African American Mothers' and Children's Racial Centrality From Elementary Through High School [18]. For example in diagnosing Parkinson's disease [19] eye tremor movement that was extracted from the recorde eye position signal. Kisi [20] used the AR model to predict stream flow. Other researchers Zhao, Morgan, and Davis [21] used the AR model to classify the output from gas chromatography. Lee and Chon [22] used the AR model to model the extraction of respiratory rate. Figueiredo and Figueiras [23] used the AR model to detect damage. Kim, Faloutsos, and Yang [24] used the AR model to predict EEG data related to epilepsy. Study in brain science found the problem with playing games among driver using AR model Jayawardhana et al. [14] used the AR model to identify structural damage. Zhang, Qi, and Li [9] used the AR modelto simulate dynamic light scattering (DLS) signals. Zhao et al. [10] used the AR model to predict channels in wireless networks. Dai, Liu, and Zhang [11] applied the AR model to the preearthquake ionospheric anomaly analysis. Yuewen et al. [12] used the AR model to predict the engine's exhaust gas main engine
temperature. The AR model can predict the changing trend of smoke temperature. Song [13] used the AR model to identify the
frequency of random signals. Kaewwit, Lursinsap, and Sophatsathit [14] used the AR model to determine the high accuracy of biometric electroencephalography (EEG). Padmavathi and
A study on the optimum order of autoregressive models for heart rate variability (HRV) [25] AR-based Method for ECG Classification and Patient Recognition The electrocardiogram (ECG) is the recording of heart activity obtained by measuring the signals from electrical contacts placed on the skin of the patient. By analyzing ECG, it is possible to detect the rate and consistency of heartbeats and identify possible irregularities in heart operation. This paper describes a set of techniques employed to pre-process the ECG signals and extract a set of features – autoregressive (AR) signal parameters used to characterise ECG signal. Extracted parameters are in this work used to accomplish two tasks. Firstly, AR features belonging to each ECG signal are classified in groups corresponding to three different heart conditions – normal, arrhythmia and ventricular arrhythmia. Obtained classification results indicate accurate, zero-error classification of patients according to their heart condition using the proposed method. Sets of extracted AR coefficients are then extended by adding an additional parameter – power of AR modelling error and a suitability of developed technique for individual patient identification is investigated [26]. Burr and Cowan. Autoregressive time series model-based spectral estimates of heart period sequences can provide a parsimonious and visually attractive representation of the dynamics of interbeat

intervals. While a corollary to Weld's decompo- sition theorem implies that the discrete Fourier periodogram spectral estimate and the autoregressive spectral estimate converge asymptotically, there are practical differences between the two approaches when applied to short blocks of data. Autoregressive spectra can achieve good frequency resolution and excellent statistical stability on short segments of heart period data of sinus origin. How- ever, the order of the autoregressive model (number of free parameters to be estimated) must be explicitly chosen, a decision that influences the trade-off of frequency resolution with statistical stability. Akaike's Information Criterion (AIC), an information-theoretic rule for picking the optimum order, is sensitive to the aggregate amount of data in the analysis. Thus, the best model order for estimating the spectrum of a 4-minute segment of data will generally be lower than the best order for estimating an hourly spectrum based on averaging I5 4- minute spectra. A major advantage of the autoregressive model approach to spectral analysis is the ease with which it can be extended to handle messy data frequently seen in heart rate variability (HRV) studies. A number of autoregressive- based robust-resistant techniques are available for the analysis of heart period sequences that contain a high volume of nonsinus and other unusual beats intervals. A theoretically satisfying framework is also available for spectral analysis of unevenly sampled data and missing data [27]. Detection of Atrial Fibrillation using Autoregressive modeling

Padmavathi and Ramakrishna. Atrial fibrillation (AF) is the common arrhythmia that causes death in the adults. We measured AR coefficients using Burgs method for each 15 second segment of ECG. These features are classified using the different statistical classifiers: kernel SVM and KNN classifier. The performance of the algorithm was evaluated on signals from MIT-BIH Atrial Fibrillation Database. The effect of AR model order and data length was tested on the classification results. This method shows better results can be used for practical use in the clinics [28]. Some researchers studied the feasibility of the improved prediction of heart motion. they propose a nonlinear time varying multivariate vector utoregre sive (MVAR) model based adaptive prediction method. In this model, the significant correlation between ECG and heart motion enables the improvement of the prediction of sharp changes in heart motion and the approximation of the motion with sufficient detail. Last, they [29]. Ge, Hou, and Xiang offers a formulation to many problems more realistic than that of classical hypothesis testing or of criteria based on estimation theory (e.g., AIC) in autoregressive model. The experimenter is also allowed to incorporate any a priori knowledge of the true order (e.g., lower bound as well as upper bound) [30]. Study of Feature Extraction Based on Autoregressive Modeling in ECG Automatic Diagnosis. Ding-Fei, Bei-Ping, and Xin-Jian. This article explores the ability of multivariate autoregressive model (MAR) and scalar AR model to extract the features from two-lead electrocardiogram signals in order to classify certain cardiac arrhythmias. The classification performance of four different ECG feature sets based on the model coefficients are shown. The data in the analysis including normal sinus rhythm, atria premature contraction, premature ventricular contraction, ventricular tachycardia, ventricular fibrillation and super ventricular tachycardia is obtained from the MIT-BIH database. The classification is performed using a quadratic discriminant function. The results show the MAR coefficients produce the best results among the four ECG representations and the MAR modeling is a useful classification and diagnosis tool[31]. Takalo, Hytti, and Ihalainen explained the theoretical basis of autoregressive (AR) modelling in spectral analysis is explained in simple terms Spectral analysis gives information about the frequency content and sources of variation in a time series. The AR method is an alternative to discrete Fourier transform, and the method of choice for high-resolution spectral estimation of a short time series. In biomedical engineering, AR modelling is used especially in the spectral analysis of heart rate variability (HRV) and electroencephalogram tracings. In AR modelling, each value of a time series is regressed on its past values. The number of past values used is called the model order. An AR model or process may be used in either process synthesis or process analysis, each of which can be regarded as a filter. The AR analysis filter divides the time series into two additive components, the predictable time series and the prediction error sequence. When the prediction error sequence has been separated from the modelled time series, the AR model can be inverted, and the prediction or sequence can be regarded as an input and the measured time series as an output to the AR synthesis filter. When a time series passes through a filter, its amplitudes of frequencies are rescaled.

The properties of the AR synthesis filter are used to determine the amplitude and frequency of the different components of a time series. Heart rate variability (HRV) data are here used to illustrate the method of AR spectral analysis. Some basic definitions of discrete-time signals, necessary for understanding of the content of the paper, are also presented [32]. However the heart beat research in South East Asia were very rare. Most research conducted in western countries. In this research we purpose the mathematical modelling for adolescents who live in collectivistic culture, and different emotional response with western countries.

2. Method

in this research the heart rate of eight adolescents male and female were recorded, living at rent room or house on self-selected sleep-wake schedules. Individual differences in human biological rhythms and diurnal preference (morningness-eveningness) are often based on self-report scales. All subjects were adolescents Indonesian muslims. Faithful Muslims usually has diurnal preference in early morning. the daily mood, physical activities, and waking hours were recorded too. Several subjects filled their questionaire faster than others.

The fast and bright subject usually have morningness preference. Indonesia as muslims country, has different kind of muslim population. Some of them wake up early for morning prayers, and some don't. Some people just say that they were muslim, but they don't understand their religious teaching. So they don't practice daily prayer. The adolescents muslims that practice five times prayers were recruited in this research.The reversible jump MCMC algorithm is used to identify the AR model order and the AR model parameter for the simulated data.

3. Results and Discussion

Studies on heart or heart rate in international publications mostly in western world with its different races and cultures [33][34]. This study was different with what Liang, Meng, and Yu used multivariate autoregressive model. They used Multivariate Autoregressive Model Based Heart Motion Prediction Approach for beating heart during surgery. Then, they investigate the relationship between ECG signal and beating heart motion using Granger Causality Analysis, which describes

A simulation study is conducted to find out whether the performance of the reversible jump MCMC algorithm worked well or not. To know the performance of reversible jump MCMC algorithm simulation study is conducted. Figure 1 is an AR heart rate data made according to the equation (1) with n = 100.

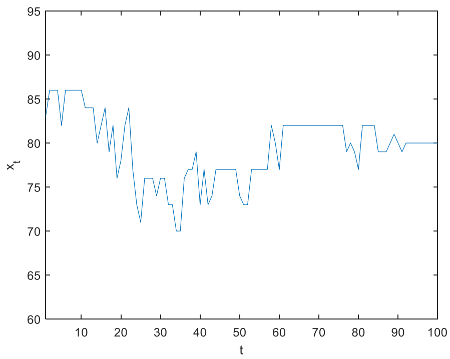

Fig. 1: Heart Rate of the adolescent girl

The reversible jump MCMC algorithm is implemented in this heart rate of the adolescent girl who wake up in early morning regularly and does household activities to estimate the AR model order, AR model coefficients, and error variance. Figure 2 shows the histogram of the AR model order

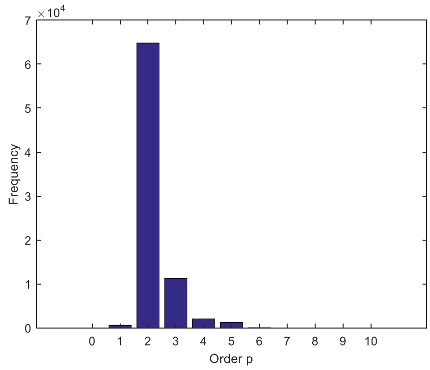

Fig. 2: Histogram of the AR Order of adolescent girl

Figure 2 shows that the mode of AR order is reached in order 2. This means that the estimator for AR order is p = 2. After it is determined that the most suitable AR model is AR (2) then the estimator for the AR coefficient and corresponding error variance is determined.

Heart rate mathematical model is given following equation (1)

$$x_t = 0.2\, x_{t-1} + 0.78\, x_{t-2} \quad (1)$$

Data I: The pulse of girls with activities at home

Figure 1 depicts the human pulse. The number of pulses per minute is recorded for 100 minutes. For data I, the histogram shows that the maximum order is reached in number 2. So the estimation for the autoregressive model order is 2. While the estimated coefficients are 0.2 and 0.78. So that the following equation is obtained

$$x_t = 0.2\, x_{t-1} + 0.78\, x_{t-2}$$

These mathematical equations can be used for several purposes.

First, the equation can be used to predict the next pulse. For example, the 101st pulse prediction can be calculated by the following equation

$$x_{101} = 0.2\, x_{100} + 0.78\, x_{99}$$

Because $x_{99} = 80$ dan $x_{100} = 80$ the prediction of the 101st pulse is

$$x_{101} = 0.2(80) + 0.78\,(80) = 78$$

Figures

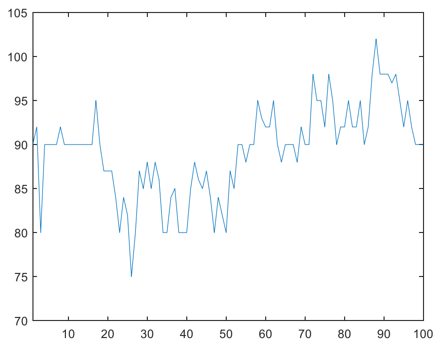

Fig. 3: Heart rate adolescent boy

The reversible jump MCMC algorithm is implemented in this heart rate of the adolescent boy who wake up in early morning and late morning irregularly and does outdoor activities to estimate the AR model order, AR model coefficients, and error variance. Figure 4 shows the histogram of the AR model order

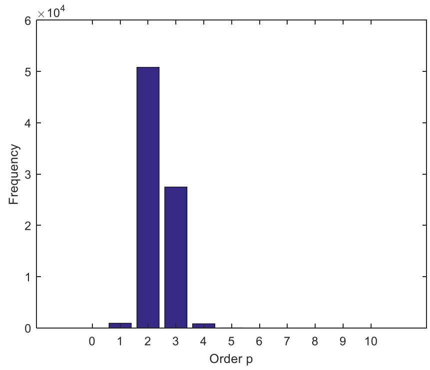

Fig. 4: Histogram of the AR Order of adolescent boy

Figure 4 shows that the mode of AR order is reached in order 3. This means that the estimator for AR order is p = 2. After it is determined that the most suitable AR model is AR (2) then the estimator for the AR coefficient and corresponding error variance is determined

Heart rate mathematical model is given following equation

$$x_t = 0.34\, x_{t-1} + 0.64\, x_{t-2} \qquad (2)$$

The equation (1) and (2) showed that there is differrent heart rate pattern between the girl and boy. The girl wake up early in the morning (chronotype preference: early morning) and doing her activities at home. While the boy has an outdoor activities. The similar AR Order

Figure 2 and Figure 4 show that the mode of AR order are reached in order 2. This means that the estimator for AR order is p = 2. There is something similar for both subject. Either they are both human or something else. The natural light seems influence their heart beat. From the eight subject, they have almost different pattern in their mathematical models. The active subjects in daily morning prayer (praying on time) have better record. Daily mood also affects the subjects' heart beat.

From our data, we found that the heart rate of an adolescent vary according to their moods and activities. One of adolescent felt dizzy after eating with normal heart rate while in other time he felt comfortable. The possible explanation was the overeating will cause dizziness. Before and after prayer showed low heart beat and high one. During comfortable conditions the adolescent score different heart rate depend on their activities.

Fry (1994) points out that relaxing laughter gives rise to a significant increase in heart rate, so that for normal hearts it brings diverse benefits for the heart muscle, similar to those obtained from any aerobic exercise[35].

The mechanism of the influence of humor on physical health, explained by Martin (2001) as follows (each related to various types of humor):

- Laughter can train and relax muscles, improve breathing, stimulate circulation, increase endorphins production, reduce stress related hormones and enhance the immune system.

- Humor and laughter can encourage positive emotional states, which will have beneficial effects on health, such as increasing tolerance to pain, enhancing the immune system and avoiding the consequences of negative emotions at the cardiovascular level. According to this model, laughter is not important to get health benefits, because humor induces a positive mood with or without laughter.

- Humor can be beneficial to health indirectly by moderating the adverse effects of stress on health. The experience of stress in a person's daily life can damage health, for example by suppressing the immune system and increasing the risk of infectious diseases and heart disease. According to this model, the cognitive-perceptual component is more important than just laughter, and the ability to see the funny side in bad times[36].

4. Conclusion

The conclusion is that the order two see figure 3 showed there are similar patterns. It showed histogram that placed on number two. From this finding researcher can predict that the amount of the next beat can be predicted from two numbers before the end of this number the last number. The research comparison should be conducted.

This study has limitations, the most important of which is the accuracy of data about positive and negative affect experiences that underlie the mood of the subject. Future studies may be included in the process of measuring positive and negative effects of research subjects using the Positive And Negative Affect Scale (PANAS; Watson, Clark, & Tellegen, 1988)[4]
The PANAS is composed of 20 items and yields separate scores for positive and negative affect. Examples of positive items include “interested,” “strong,” and “enthusiastic.” Negative items include “distressed,” “upset,” and “guilty.” Each item is rated on a 5-point scale, as experienced in the present moment, with a range from 1 (very slightly or not at all) to 5 (extremely). The PANAS is a well-validated, commonly used measure of both positive and negative affect[4].

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